ANALYZING THE SPILLOVER MECHANISM ON THE SEMICONDUCTOR INDUSTRY IN THE SILICON VALLEY AND ROUTE 128

by

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Abstract

To understand the impact of science and engineering innovations on economic growth requires relating discoveries to products, and identifying the scientists and engineers who are responsible for the knowledge transfer. Studies reliant on geographic proximity alone can show only that economic activity varies positively with the amount of research being done at a university. [David (1992), Nelson and Romer (1996), Jaffe (1989,93)]. These “geographically localized knowledge spillovers” have proved unable to explain what it is about research universities that is crucial for their local economic impact (training, the research findings?) and, therefore, are unconvincing both to policy makers and the public.

This paper analyses the spillover mechanism identifying its main components by analyzing the effect of university-based star scientists through explicit and implicit ties, and the effect of other neighbor firms, on the performance of semiconductor enterprises measured with patents. Explicit ties are modeled by the full and part-time job mobility of scientists located in universities; and implicit ties, by the presence of positive externalities or spillover effects to the firms of untied scientists at Universities in the same economic area. Specifically, this study examines the Silicon Valley and Route 128 cases in detail identifying the differences and similarities between these two major semiconductor regions in their spillover mechanisms.

Previous research on high-technology industries has demonstrated the importance of geographically localized “knowledge spillovers” by building specific links between university scientists and firms and estimating the local effects of different types of links. This research goes an step forward, by not only measuring the effect of University research through the direct ties to firms (Zucker, Darby, Armstrong; 1998); but also measuring the importance of the inside industry R&D spillovers in the growth of the region.

JEL: 012, 034,033, O32, L20,L22, L20, L63

1. Introduction

When analyzing the development of high-technological sectors there is a common pattern observed: the regional concentration of Industrial sectors. Explanations go from the presence of big cities [Vernon, Henderson, Ari Kuncoro and Matt Turner (1995)], to the presence of top quality Universities, and therefore the presence of knowledge spillovers (Nancy Dorfman, 1983; Daniel Shimshoni, 1966; P.Teplitz, 1965, Jaffe, 1986 and AER 1989). Even though, there had been no effort in trying to model the spillover mechanism.

To understand the impact of science and engineering innovations on economic growth requires relating discoveries to products, and identifying the scientists and engineers who are responsible for the knowledge transfer. Studies reliant on geographic proximity alone can show only that economic activity varies positively with the amount of research being done at a university [David (1992), Nelson and Romer (1996), Jaffe (1989,93), Zucker, Darby, Brewer (1998)]. These “geographically localized knowledge spillovers” have proved unable to explain how and what it is about research in universities that is crucial for their local economic impact (training, the research findings?) and, therefore, are unconvincing both to policy makers and the public.

Previous research on high-technology industries has demonstrated the importance of geographically local “knowledge spillovers”. Knowledge spillovers are central to the Romer (1986), Lucas (1988), Aghion and Howitt (1992), and Grossman and Helpman (1992) growth models. Compatible with these models of economic growth, spatial spillovers between university research and the high technology sector have already been analyzed in the familiar Griliches-Jaffe knowledge production function [Jaffe (1989)].

Other economic growth models have taken the specific form of external learning by doing, as in Lucas (1988, 1993), Stokey (1988), and Young (1991, 1993). Especially relevant is Lucas'

(1993) conclusion that learning by doing is a prime candidate to explain the incredible growth observed, for example, in South Korea over the last three decades.

Compatible with these economic models of growth, recent evidence on the process of learning, specifically through the working relationships of scientists from universities to firms, has only recently been examined for biotechnology [Zucker and Darby 1996; Zucker, Darby and Armstrong (1997); see also Zucker, Darby and Brewer (1997)]. The first two of these papers provide evidence that "spillovers" appear to explain the transfer process only when the variables that measure working relations between university and firm scientists are absent, thus providing empirical evidence that a market relationship between university scientists and firms explains the observed technology transfer.

In this research we plan to extend the strong results obtained in Zucker, Darby, and Brewer (1998) and Zucker, Darby and Armstrong (1998) to the semiconductor sector and go a step forward. It will not only measure the effect of university research through the direct ties to firms; but also measures the importance in the growth of the region of the indirect effect by the inside industry R&D spillovers. It will identify local knowledge spillovers, and actually decompose them in three different sources of spillovers. First, specific links of stars to the research done and products developed and manufactured in commercial enterprises; second, indirect effects in the industry just because of the closeness to the universities and not acquainted by the specific links. Finally, we will also identify the presence of inside industry spillovers by identifying the effects of neighbor firms over the performance of a specific company.

The major focus will be therefore on unwrapping and detailing the components of the spillover mechanism to firms in the semiconductor industry, comparing these relationships in Silicon Valley and Route 128.[1] While case studies already document the important role of

[1] Other advantages of working with semiconductors and this two specific regions are: their innovation is mostly with common origins in university-based research (MIT and Stanford); there are two main periods of start-ups: early 1970’s and early 1980’s; two different innovation and diffusion strategies that clearly demonstrates that regions industrial strength depends on more than just the proximity of its firms.

universities in both areas[2], these two areas developed different trajectories according to systematic case studies conducted by Saxenian (1996). She argues that Silicon Valley's lack of a prior industrial history and its distance from established economic and political institutions facilitated experimentation with novel and productive relationships, leading to more open and reciprocal ties between Stanford and local industry than existed in the Route 128 region.

Examining actual working relationships between university scientists and firms can test this difference, and in so doing, shed light on the issue of the importance of these kinds of relationships in technology transfer. In other words, the differences between Silicon Valley and Route 128 constitute a natural experiment, and thus permit a direct comparison of the effects of the kinds and amounts of working relationships on technology transfer to new firms that grew up in both regions. The effects of these relationships on consequent success of the firms, and hence on regional development, will also be examined, following the techniques developed in Zucker, Darby and Armstrong (1997). Additionally, we will go a step forward, by also measuring the importance of the inside industry R&D spillovers in the success of companies.

In the first section, a detailed explanation of the theoretical model behind this paper is outlined. Then a detailed explanation of the estimation methodology and how the explicit and implicit ties are identified and the econometric techniques used. Section four describes the data collected and how this research exploits the requirement that patents cite relevant prior patents and scientific literature to develop a network of linkages between the most prominent scientists and firms for the semiconductor sector. Finally the empirical findings are detailed.

2. The Model

The timing of innovation plays a crucial role in the marketplace. There are two reasons why [Shy, (1995)], in most cases, a firm that is first to discover a new technology or a new product gains an advantage over competing firms: First, the firm is eligible to obtain a patent

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[2] See Jaffe, (1989).

protection that would result in earning monopoly profits for several years. Second, consumers associate the innovator with a higher-quality producer and will therefore be willing to pay a higher amount for the brand associated with the innovator.

Given the significance of becoming the first to discover, firms invest large sums in R&D, knowing that not discovering or discovering too late may result in a net loss from the innovation process. In this section we try to model the behavior on the R&D decision process of firms and how the spillover mechanism works to be able to unwrap and detail the main elements inside the spillover mechanism.

Modeling the Expenditures in R&D and the Spillover Mechanism

In this section, we do not address problems such as how firms manage to implicitly or explicitly coordinate their research efforts and how the research information is shared by the participating firms [see Combs (1993) and Gandal and Scotchmer (1993)]. Instead, we analyze how firms determine their research efforts, under cooperation and no cooperation, and taking in to consideration that they compete in the final good's market after the research is completed. This problem has been the subject of many papers [see Choi (1993); d'Aspremont and Jacqemin (1988); Kamien, Mullerm and Zang (1992); Katz (1986), Katz and Ordover (1990)].

Assuming firms are engaged in a Cournot quantity game in a market for a homogenous product, where the demand function is given by $p=100-Q$. We denote by $f(x_i)$ the amount of R&D undertaken by firm i, $i=1,2$, and by $c_i(x_1,x_2)$ the unit production cost of firm i, which is assumed to be a function of the R&D investment levels of both firms, formally, let:

$$c_i(x_1, x_2) \equiv 50 - f(x_i) - \beta f(x_j) \quad i \neq j, i = 1,2, \beta \geq 0 \qquad (1)$$

That is, the unit production cost of each firm declines with the R&D of both firms, where the parameter b measures the effect of firm *j's* R&D level on the unit production cost of firm *i*.

Formally we say that R&D technologies exhibit (positive) spillover effects if $b > 0$. That is, if $b > 0$, the R&D of each firm reduces the unit cost of both firms. For example, spillover effects occur when some discoveries are made public during the innovation process (some secrets are not kept),[3] or when there is share of information as occur in Silicon Valley [see Saxenian (1996)].

Also, this positive externality can emerge from the labs investing in infrastructure or from research institutes and universities that benefit all other firms as well [see Jaffe (1986) for empirical evidence], to capture this effect we define the $f(x_i)$ function. The amount of R&D firm *i* will invest is a function of direct investment in R&D (e) as well as it will decline with the presence of positive spillovers from the universities around (u). Therefore $f(x_i)$ can be expressed as:

$$x_i = e + \phi u, \quad \phi > 0 \qquad (2)$$

where *e* refers to real cost saving R&D expenditures by the firms which could include investments in research labs as in human capital, and *u* is the investment in R&D by universities in the same region, where if $\phi > 0$ there will be positive spillovers from the universities. At the same time this university positive spillovers will affect the spillovers from firm j through its $f(x_j)$ function.

It is important to mention that given it is difficult to identify the magnitude of *e* it is normally measured with error, attributing it as part of the spillovers a company receives.

Therefore the spillover mechanism can be open in two major sources, the effect from universities and the effect from other firms, and can be expressed in the following equation:

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[3] Assuming $b > 0$ implies that R&D exhibits only positive spillover effects. However, note that in some cases b can be negative if the R&D of a firm involves vandalism activities against competing firms, such as radar jamming or spreading false information and computer viruses.

$$c_i(x_1, x_2) \equiv 50 - [e + \phi u] - \beta f(x_j) \quad i \neq j, i = 1,2, \beta \geq 0, \phi > 0 \qquad (3)$$

Finally, to close the model we need to assume that R&D is costly to firms. Formally, denote $TC_i(x_i)$ the cost (for firm *i*) of operating an R&D lab at a research level of x_i, and that research labs operate under decreasing return to scale. Formally,

$$TC_i(x_i) = \frac{(x_i)^2}{2} \qquad (4)$$

The decreasing return to scale assumption implies that the cost per unit of R&D increases with the size of the lab. That is, higher R&D levels require proportionally higher cost of lab operation. This assumption heavily affects the result. If labs were to operate under increasing returns (say, by having to pay a high fixed cost for the construction of the lab), firms would always benefit from operating only a single lab (that serves both firms) when they are allowed to cooperate in R&D.

The objective therefore of our empirical application will be to try to model the importance of the positive spillover effect from other firms (β) and the spillover effect from universities (ϕ). As well, we will try to identify the magnitude of *e* through the investment the companies do in human capital. The next section will detail the methodology and the econometric model to be able to attain this objective.

3. Methodology and the Econometric Model

The methodology followed can be divided in two main stages. The first, which is part of joint work with Zucker and Darby, consist in identifying the top scientists (stars) and the identification of their relationship with firms and how important they are in explaining the birth of new semiconductor firms. With this purpose, we will do the analysis for the whole U.S., and once we identify the star scientists and validate their importance we will concentrate on the spillover analysis for our two regions of interest: Silicon Valley and Route 128. In these two regions we will measure the effects of the universities on the region by the decomposition of the local spillovers in three major components: direct links effect, indirect effects of universities in the region, and inside industry spillovers.

To identify the top scientists as well as the ties to firms, this research exploits the requirement that patents cite relevant prior patents and scientific literature. This information is used to identify the citations to scientist that had been inventors of a semiconductor patent. From the citations counts the most cited scientists can be identified as the star scientists as detailed in section 4, where the data is described.

Additionally, by looking at the information of their affiliations, their co-inventors affiliations, and the institutions to which this patents are assigned, it allows to develop a network of linkages between the most prominent scientists and firms for the semiconductor sector.

To measure the effects of the university to the semiconductor industry and to the region the following successive stages of estimation are developed which allow to decompose and to identify the magnitude of what normally had been referred as local spillovers. In the first stage the work done by Zucker, Darby, & Armstrong (1997) is followed, to examine the effect of university-based scientists on one measures of performance of the semiconductor industry: number of patents granted to semiconductor manufacturing discoveries by a firm.

After identifying the direct effects of universities through specific links to firms we will try to measure the local geographic effect of neighbor firms to the semiconductor industry introducing several alternatives to Jaffe's(1989) indicators. Specifically we will identify the effect of neighbor firms in a spatial econometric approach [see: Anselin(1988,1990), and Anselin, Varga, Acs (1996)] in trying to formalize the spatial extent of the geographic spillovers not captured by the direct ties, by means of the so-called spatial lag variables. These variables capture the research activities in concentric rings within the 3 digit zipcode sub-regions. Specifically we will explicitly consider the potential for spatial autocorrelation[4] by both testing for the presence of spatial effects and by implementing models that incorporate it as a way of measuring this indirect spillover effect from other firms.

The Econometric Model

To measure the effects of the universities to the semiconductor industry and to the region the following successive stages of estimation will be carried:

A. Birth equation:

In this stage, following Zucker, Darby and Brewer(1998), we will model the birth of new semiconductor firms for the whole U.S. to validate the importance star scientists on this industry, the estimation equation can be expressed as follows:

$$Y_{i,t} = \alpha_0 + \beta_1 AStars_{i,t} + \beta_2 Ventcap_{i,t} + \beta_3 Univ_{i,t} + \beta_4 Z_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $Y_{i,t}$ is the number of firm births in region i in year t, $AStars_{i,t}$ is the number of active star scientists in region i and year t. A star scientists will be active if she/he was cited by any semiconductor patent in the current year. $Ventcap_{i,t}$ is the total number of eligible venture capital firms in region i in year t. $Univ_{i,t}$ consist of two variables that measure the presence of university R&D in the region: number of top quality universities in the region i and year t, and number of scientists in all semiconductor relevant department in BEA area i supported by a research grant (see section 4 for details). Finally, $Z_{i,t}$ are variables to control for regional effects, as macroeconomic variables for the region.

[4] Spatial autocorrelation says that what it is observed in one place is in part determined by what is occurring in the other spatial locations.

B. Unwrapping the Spillover Mechanisms

Following our theoretical framework, in this section we will try to identify the direct investment of companies in human capital (e), as well as the spillover effect from universities (ϕ), and the spillover effect from firms (β). With this objective we will carry an analysis for two of the major areas for the semiconductor industry: Silicon Valley and Route 128. At the same time, we will try to identify empirically the differences in the spillover process between these two regions. This stage will consist mainly of two estimations, the first one will identify the direct and indirect links of star scientists, and the second one will model the inside industry effect by identifying the effect over the performance of a company of star scientists in neighbor companies.

B.1. Identifying Direct Link Effects:

In this stage we measure the effect of university based scientists one measure of performance [Zucker, Darby & Armstrong (1998)]: number of patents granted in manufacturing of semiconductors for company i.. The equation to be estimated can be expressed as following:

$$\text{Performance}_{i,t} = \alpha_0 + \beta_1 \text{UntiedStars}_{i,t-1} + \beta_2 \text{TiedStars}_{i,t-1} + \beta_3 Z_{i,t} + \varepsilon_{j,t} \qquad (6)$$

where *i* refers to the specific firm, and *t* refers to the specific year. Untied Stars are patent weighted stars that report a university or a research institute as the assignee of the patent and have no formal relationship with the firm. On the other hand, TiedSars are patent weighted stars in which the assignee is a firm. Finally, Z represents the age and age square of the firm, as a control experience of the firm in the semiconductor industry.

B.2. Indirect effects: Inside Industry effect

Here the dependence from the neighbor firms will be measured. Expressing the model above in matrix form and including the neighbor effect:

$$\text{Performance} = \alpha + \rho W \cdot \text{tiedStars} + \beta_1 \text{UntiedStars} + \beta_2 \text{TiedStars} + \beta_3 Z + \varepsilon \qquad (7)$$

For N firms observed, $\boldsymbol{W_i}$ is the ith row of an (N*N) matrix $\boldsymbol{W}$ that assigns to each firm its neighbors. The $\boldsymbol{W}$ used here can be characterized: $W=\{w_{ij}\}$ such that $w_{ij}=1$ if i and j are neighbors, $w_{ij}=0$ otherwise, and $w_{ii}=0$ for all i. The rows of W are then normalized such that each observations' neighbors have the same amount of influence, that is $\sum_j w_{ij} = 1$, for all i. In addition it will be assumed that each neighbor of a given firm carries equal weight, $w_{ij=}$ w_{ik} for non-zero elements (neighbors) k and j for firm i. If more information were available about the amount of influence each firm yields, this could be incorporated into the W matrix [regarding the different structures, see Anselin (1988)]. *W.TiedStars* can be considered as a weighted average of the effect of tied stars at "neighborhood" locations.

4. Database Development

This research consists mainly of five databases. First, the patent database including issue date, application date, patent holder, address, name inventors and their addresses, and all prior patents and scientific literature cited in the patent relevant to the manufacturing of semiconductors was obtained from CHI Research Inc. and complemented with information from the U.S. Patent and Trademark office online data set (see data sources). The data set consists of 59,782 patents on semiconductors granted between 1973 and 1997. Figure 1.1, shows the evolution of the patents granted by application year (reason of the small number in 1996 because we just have patents granted up to 1997). From this graph is clear the substantial growth trend of patents granted during this period (6.6% in average per year).

This database of patents has a dual purpose in this research. On one hand it allows us to identify the most cited inventors in semiconductors ("star") and, on the other hand, it will allow, given the information on inventors and assignees, to build the database of links between universities and firms. Based on the citations counts for the inventors, 414 leading researchers (“stars”) were identified, that list at least one time a U.S. address using a cutoff of 100 or more citations in our semiconductor patent data set. In addition collaborators for the stars and other (neither stars nor collaborators) where identified. Figure 1.2, shows the evolution of “star” scientists according to the date in which they where first cited. Additionally, a star was defined as active in an specific year if she/he received a citation from another patent in the semiconductor area during that year.

Secondly, the firm data set, for which we had collected information on 1239 firms was mainly obtained from the Harris Info Source Selectory Manufacturers Database, and was complemented with information from different directories to be able to build a panel data set (see data sources). The information collected can be classified in three categories. The first one consists mainly of the basic information of the firm including: name, location, date of birth (or entry to semiconductors for sub units of preexisting firms), type of ownership, and other generic information of the company. The second, consists mainly of different measures of output in the electronic divisions of the companies in our database. This section will include time series since 1970 or date of birth, if later than 1970, and other characteristics of the firms. Finally specific names of officers and executives, as well as members of scientific advisory boards for firms making initial public offerings or other public disclosure are collected, as a way to identify possible ties with the star scientists.

Figure 1.2, shows the evolution of these semiconductor start-ups by date of entry. As shown in Figure 1.2, there is a reduction in the number of entrants in 1975, consistent to the decline in the demand documented in Brittain and Freeman[5]. In the later 70’s, star-up companies began focusing on market-niche strategies and reduce high cost of capital in setting up manufacturing facilities, by subcontracting the manufacturing stage to the product firms, usually large incumbents. These efforts were reflected by a new inflow of start-ups into the industry, reaching its peak in 1983 (see Figure 1.2).

5 Brittain, Jack, W and John H. Freeman, 1980. “Organizational Proliferation and Density Dependence Selection” in John R. Kimberly, Robert H. Miles, and Associates (eds.).*The Organizational Life Cycle*, San Francisco, CA: Jossey-Bass.

Thirdly, a university database is constructed based on the Higher Education General Information Survey (HEGIS-1973, 1975-77, 1981-84, 1993-94). This database also includes information on resources from the relevant departments for semiconductors from the NRC surveys of 1982 and 1992 as well as their measure of rankings. The departments selected for semiconductors were electrical engineering, physics, applied physics, material science, and chemistry based on information of the departments from where the stars came (see data sources).

Additionally a venture-capital firm data set is collected by extracting from the Stanley Pratt directory the name, type, location, year of founding, and interest in funding semiconductor firms. This information was extracted for all venture capital firms which were legally permitted to finance start-ups. This latter requirement eliminated a number of firms that were chartered under government programs targeted at small and minority business.

Finally, an economic data set was used from by Zucker, Darby, Brewer 1998 (see data sources) that includes total employment in the BEA area i and year t, average earnings per job in BEA area i and year t, and E/PRATIO for year t.

Figures 1.3 and 1.4, shows the geographic distribution of our main variables in the U.S. As expected star scientists are concentrated together with new firms in semiconductors. It is also important to point out the strong presence of venture capital firms where startups are.

5. Empirical Findings

Tables 1.1 to 1.7 shows the results obtained from the econometric specification detailed in section 3. As discussed in Jerry Hausman, Bronwyn H. Hall, and Grilliches (1984), the poisson process is the most appropriate statistical model for count data with significant mass of zero.

5.1 The Birth Model

Table 1.1 describes the variables used and Table 1.2 displays the major results for seven different specifications. Consistently to what Zucker, Darby and Brewer(1998) found for the biotechnology sector, we find that active stars are significant and positive in explaining the birth of semiconductor firms and its effect is ten times bigger than the effect of the other scientist. This major result is related to what can be see in figures 1.3 and 1.4, where it is clear that there is a strong and positive correlation between the star scientists and the number of firms in each BEA.

Unexpectedly the collaborators (scientists that coauthor an invention with a star scientists) have a negative and significant effect over the birth of firms. A possible explanation for this effect could be that these are lab assistants whose name appears initially as collaborators of star scientists in a not too cited patent, and which won't make any important discoveries by themselves.

When analyzing the effect of universities in the same BEA area, top quality universities in the BEA is positive and significant in Models 5 and 6, but the number of grants to faculty in these universities is significant and positive on all of our specifications. This is a clear indication of the importance of R&D research in universities in the semiconductor industry.

As expected, the number of venture capital firms is also positive and significant, showing the importance of venture capital in the birth of semiconductor companies.

Finally, the macroeconomic variables had the expected signs and significant, with the only exception of the E/PRATIO. As mentioned by Zucker, Darby and Brewer (1998) the S&P500 earnings-price ratio is a natural measure of the all-equity cost of capital in the economy and hence should enter negatively as a determinant of births, but as can be seen in Table 1.2, it enters positively and significantly. A possible explanation for this sign could be that this variables is capturing economic cycles rather than the all-equity cost of capital, and therefore a positive sign will mean that there is an increase in birth of semiconductor firms during expansions and a reduction of births during recessions.

5. 2 The Spillover Model

As mentioned previously the major contribution of this paper is to try to unwrap the spillover mechanism. With this purpose we concentrate our analysis on the Silicon Valley and Route 128. Figures 1.5 and 1.6 shows the distribution of firms and active star scientists in these two regions. As expected there is a strong concentration of firms and star scientists in these, the two most important regions of the semiconductor industry. The density of the concentration is higher in the Silicon Valley compared to Route 128, something which confirms the importance of the Silicon Valley in the semiconductor industry.

The major focus will be on the association and movement of university scientists to firms in the semiconductor industry, comparing these relationships in Silicon Valley versus Route 128[6]. While case studies already document the important role of universities in both areas (see Jaffe 1989 for a review), these two areas developed different trajectories according to systematic case studies conducted by Saxenian (1996) as shown in the following table. She argues that Silicon Valley's lack of a prior industrial history and its distance from established economic and political institutions facilitated experimentation with novel and productive relationships, leading to more open and reciprocal ties between Stanford and local industry than existed in the Route 128 region.

Saxenian does not have strong empirical measures; examining actual working relationships between university scientists and firms can test this difference, and in so doing, shed light on the issue of the importance of these kinds of relationships in technology transfer. In other words, the differences between Silicon Valley and Route 128 constitute a natural experiment, and thus permit

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[6] Other advantages of working with semiconductors and these two specific regions are: their innovation is mostrly with common origins in university-based research (MIT and Stanford); there are two main periods of start-ups: early 1970's and early 1980's; two different innovation and diffusion strategies that clearly demonstrates that regions industrial strength depends on more than just the proximity of its firms to each other.

a direct comparison of the effects of the kinds and amounts of working relationships on technology transfer to new firms that grew up in both regions.

Silicon Valley	**Route 128**
Boundaries between firms are porous	Dominated by highly self sufficient corporations
Venture capitalists were often entrepreneurs who had had made money by creating and then selling technology firms (encourage risk taking and accepted failure)	Venture capitalist who typically where financial professionals.
Were embedded in, and inseparable from intricate social and technical networks	Self sufficient corporations that preserve their independence by vertical integration
Silicon valley engineers switched firms so often that mobility became a norm.	Preferred professionals who were in it for the long term.

The results we obtained are detailed in Tables 1.3, 1.4, 1.5, 1.6 and 1.7. Table 3 mainly describes the variables we are using. From this table it can be seen that the mean number of patents per year in the Silicon Valley is practically the double of the number of patents in Route 128, as well as the presence of local ties. On the other hand, the number of untied scientists is extremely important in the case of Route 128.

The results of our econometric specification can be summarized in the following:

a. The presence of tied scientists is important in both of the regions, having a bigger coefficient for the case of the Route 128. This could confirm Saxenian's (1996) observation that companies in Route 128 tend to have more formal ties than companies in the Silicon Valley, given that they prefer to keep their information within the company boundaries.
b. Untied scientists are more important in Silicon Valley compared to Route 128, confirming our previous point. The untied scientists are a measure of the production of scientists in

universities. Although the number of patents is bigger for universities in Route 128, as shown in our results, the effect of universities around Silicon Valley over firms is much stronger. This could be an indication of the close relationships universities had, mainly Stanford, with firms in that region.

c. Cumulative ties are also significant and positive in both regions as expected, meaning that the knowledge of the scientists accumulates. But as expected the coefficients are smaller than the ties present in a specific year. An explanation to this could be the high turnover of scientists, especially in Silicon Valley, which makes more relevant to analyze the current ties rather than the accumulation of ties.

d. When desegregating the ties to Local (star in same BEA area as the firm) and external (star in a different BEA area as the firm) following Zuker, Darby, Armstrong (1998) (see Table 1.5). Local ties are significant and positive in both regions (Table 1.5) but external ties are negative and significant for Route 128, while positive and significant for the Silicon Valley. This is again a clear indicator that firms in the Silicon Valley where more willing to share information with scientists outside of their BEA while firms in Route 128 prefer to have formal local ties than external ties, and therefore the number of external ties is very small. Now when analyzing the cumulative ties, the effect for Route 128 becomes positive given that the cumulative effect of this reduced number of ties is also significant over the success of the firms.

e. Table 6, shows one of our most important results, which supports our initial hypothesis. As expected when including the effect of neighbor firms it is positive and significant. When examining separately this effect for Silicon Valley and Route 128, it is positive and significant for Silicon Valley, while is negative and not significant for Route 128. This clearly shows that firms in the Silicon Valley gain from the sharing of information from neighbor firms, while firms in Route 128 are more secretive with their ideas and human capital and therefore other firms do not obtain positive externalities from scientists working with a given company.

f. Finally, Table 1.7, included the spatially lagged dependent variable as a measure of the level of competition between companies. As expected for Route 128 this variable is positive and significant indicating a high level of competition between neighbor companies, while is negative and significant for the case of Silicon Valley.

6. Conclusions

This research validates for the semiconductor industry, specifically for Silicon Valley and Route 128, previous research on high-technology industries that demonstrated the importance of geographically local "knowledge spillovers" to the success of companies through specific links between university scientists and firms [Zucker, Darby, Armstrong (1998)].

Additionally, it helps to identify an additional element from the "knowledge spillovers" black box. We not only measure the effect of University research through the direct ties, but also measure the importance in the success of the companies of scientists at universities in the same region, and the inside industry R&D spillovers, through the influence of the scientists in neighbor firms.

This methodology, also allows us to validate some of the major differences between Silicon Valley and Route 128 that Saxenian(1996) pointed out. Thus permit a direct comparison of the effects of the kinds and amounts of working relationships on technology transfer to new firms that grew up in both regions.

In summary, the use of a linked cross-section/time-series panel data set lead to the observation that the timing and location and success of the semiconductor firms is determined primarily by intellectual capital measures, particularly the local number of highly productive scientists and their relationships to the firms. The results obtained clearly show the importance of adequate policies that allow the diffusion of this new technology from universities to firms. Furthermore, it provides a better understanding of processes underlying economic growth, and the role of the university and individual scientists and engineers in transforming the economy through the introduction and development of new discoveries and related technologies.

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8. Data Sources

Patent Data Base

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Figure 1.1
Patents Granted in the U.S. in Semiconductors Manufacturing

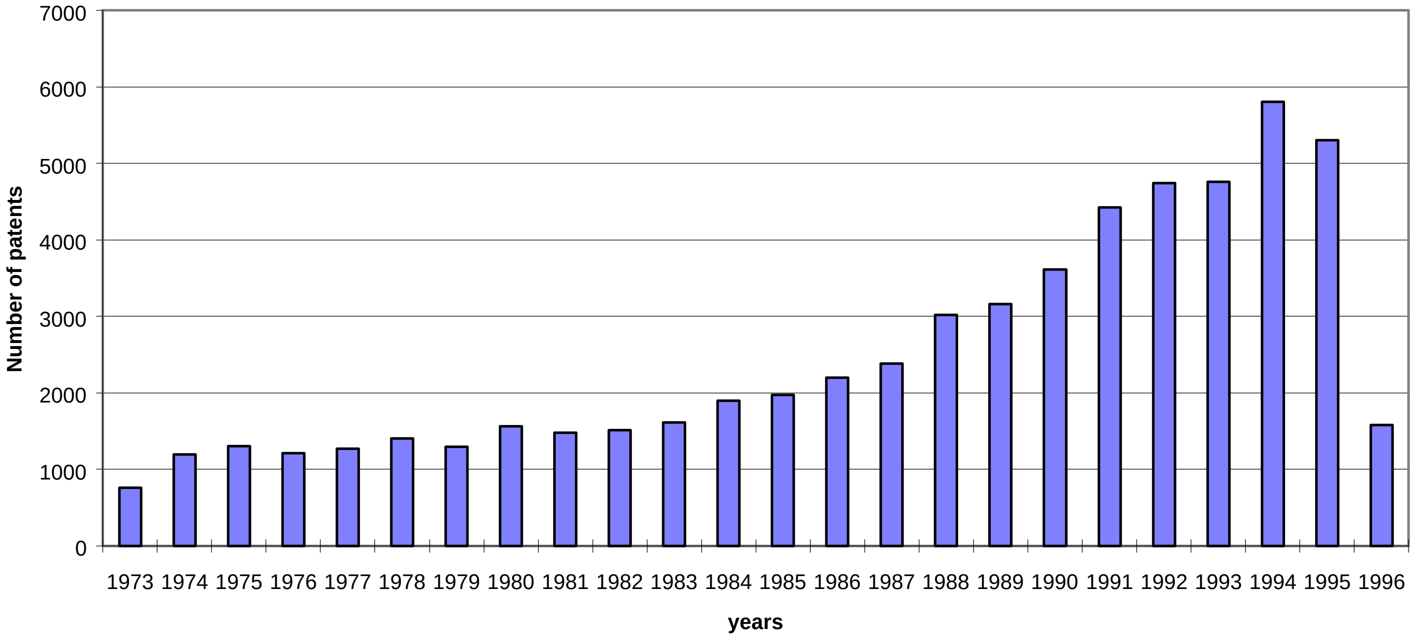

Figure 1.2
Stars and Start-ups in Semiconductors

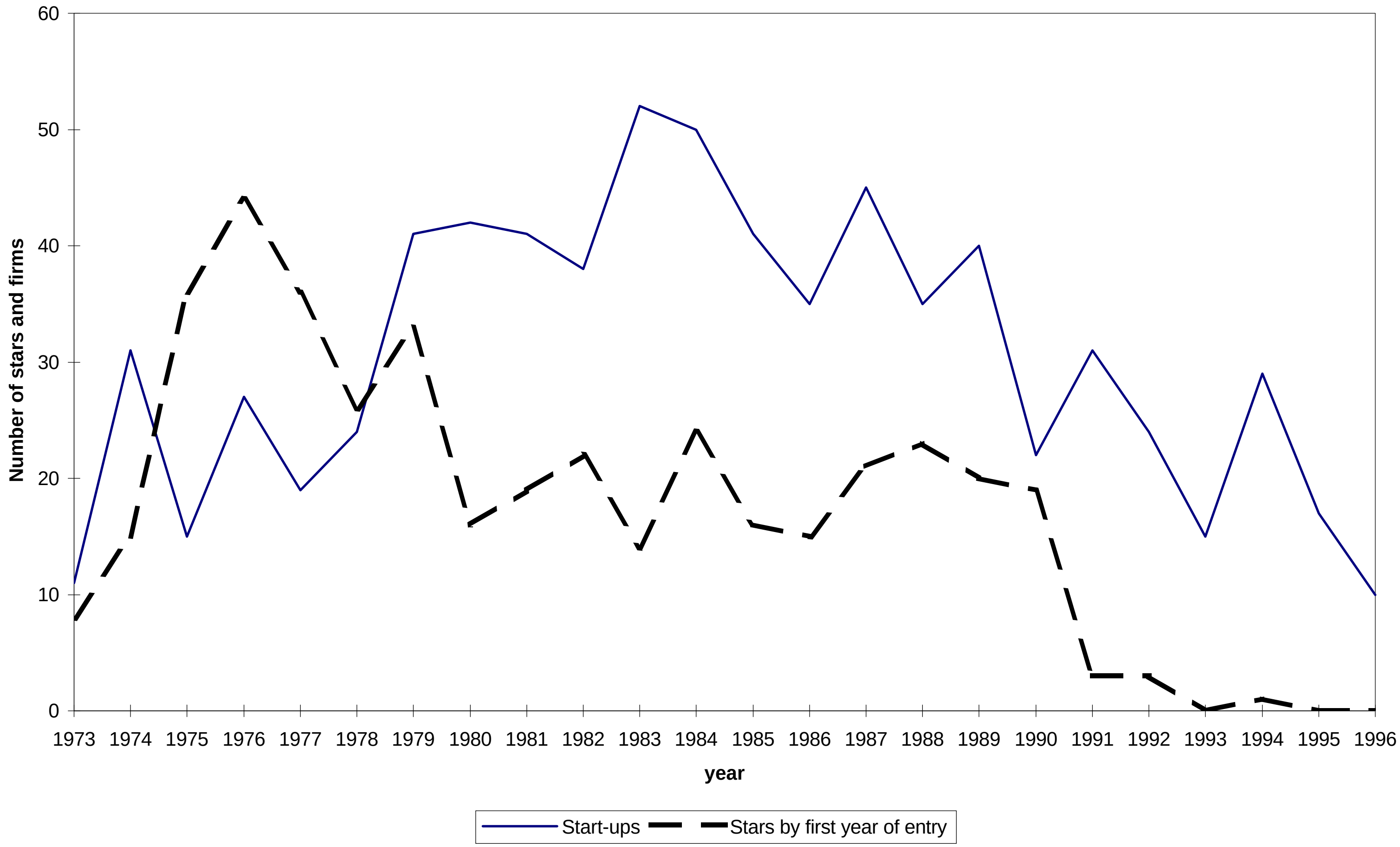

Figure 1.3
Active Stars and New Semiconductor Firms as of 1990

Figure 1.4
Active Stars, Top Quality Universities, Venture Capital Firms and New Semiconductor Firms as of 1990

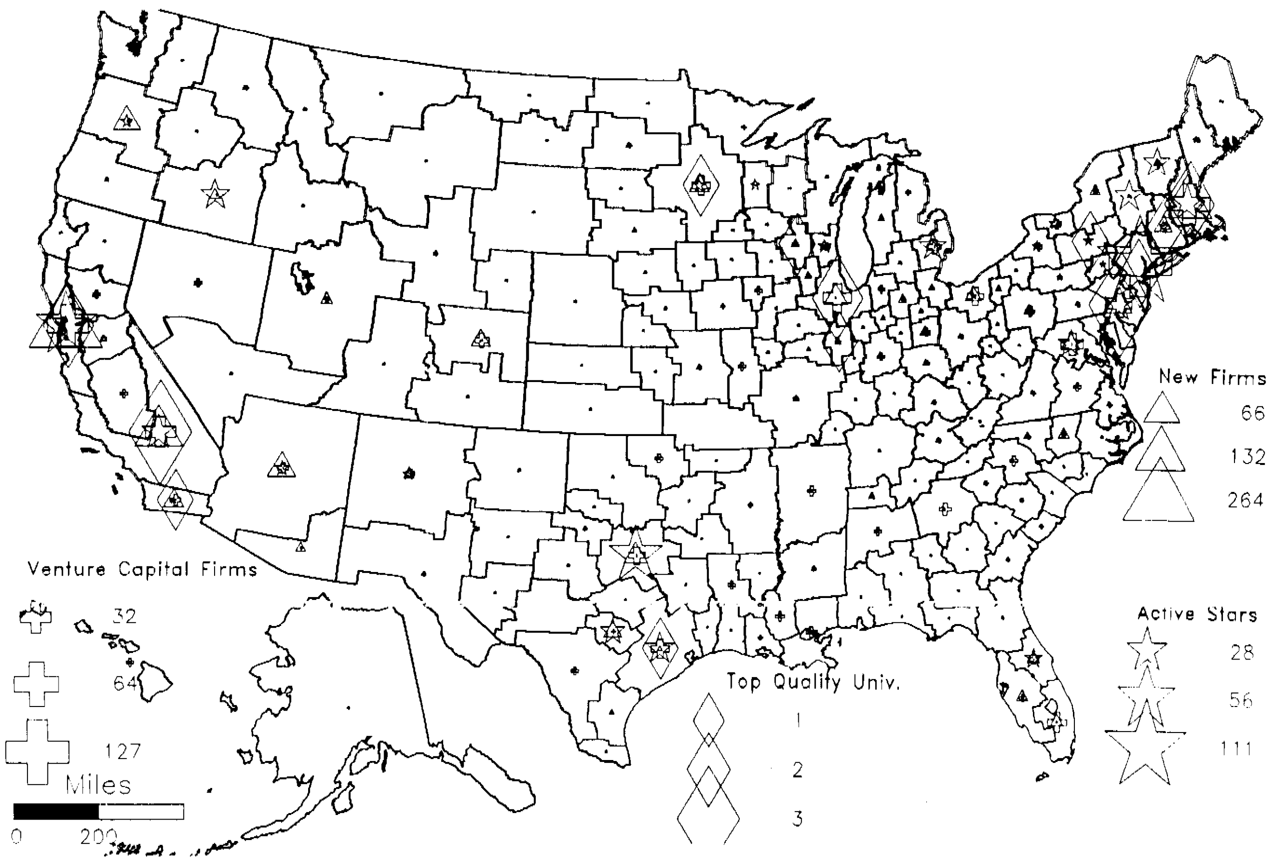

Table 1.1
Basic Statistics for the Semiconductor Industry in all the U.S.

Variable	Description	Mean	Variance
$ACTSTAR_{i,t}$	Active Stars in BEA {i} and year {t}	1.001	6.444
$ACTCOLL_{i,t}$	Active Collaborators in BEA {i} and year {t}	2.512	17.575
$ACTOTHER_{i,t}$	Other Active Scientists in BEA {i} and year {t}	9.110	45.283
$STARTUP_{i,t}$	New Semiconductor Firms in BEA {i} and year {t}	0.137	0.850
YEAR	Year	1980.000	6.056
$EJOB_{i,t}$	Average Wage & Salary Disbursements, other labor income, and proprietors income per job deflated by the implicit price deflator for personal consumption expenditures.	19229.570	2555.156
$EMP_{i,t}$	Total Employment in BEA {i} and year {t}	609615	1004733
$E/PRATIO_{t}$	Earnings/ Price Ratio for year {t}	35.456	10.178
$NTQU_{i,82,93}$	Number of Universities in a BEA with one or more most highly rated programs (rated above 4) reported by NRC surveys of 1982 and 1993.	0.125	0.468
$FACGRANT_{i,82,93}$	Total Number of Scientists in all semiconductor relevant departments in BEA area i reported by the National Research Council Survey 1982 and 1993	42.574	77.945
$VCUM_{i,t}$	Total Number of eligible venture capital firms in BEA area i in year year t	2.283	9.727

Number of Observations = 3843

Table 1.2
Poisson Regressions of Annual Births of New Semiconductor Enterprises, 1970-1990

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CONSTANT	-2.243 *	-2.459 *	-34.232	-69.176 *	-81.684 *	-185.423 *	-140.747 *
	(0.049)	(0.054)	(17.496)	(19.639)	(19.983)	(25.740)	(27.814)
$ACTSTAR_{i,t}$	0.115 *	0.116 *	0.116 *	0.058 *	0.019	0.044 *	0.134 *
	(0.008)	(0.010)	(0.010)	(0.008)	(0.010)	(0.012)	(0.018)
$ACTCOLL_{i,t}$	-0.027 *	-0.051 *	-0.051 *	-0.024 *	-0.025 *	-0.027 *	-0.041 *
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.007)
$ACTOTHER_{i,t}$		0.010 *	0.010 *	0.005 *	0.006 *	0.004 *	0.009 *
		(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$ACTSTAR_{i,t}^2$							-0.001 *
							(0.0002)
$ACTCOLL_{i,t}^2$							1.00E-04 *
							(1.00E-05)
$ACTOTHER_{i,t}^2$							-1.00E-05 *
							(2.00E-06)
TIME TREND			0.016	0.033 *	0.040 *	0.089 *	0.067 *
			(0.009)	(0.010)	(0.010)	(0.013)	(0.014)
$NTQU_{i,82,93}$				0.217	0.417 *	0.393 *	0.204
				(0.115)	(0.121)	(0.115)	(0.128)
$FACGRANT_{i,82,93}$				0.006 *	0.003 *	0.006 *	0.006 *
				(0.001)	(0.001)	(0.001)	(0.001)
$VCUM_{i,t}$					0.033 *	0.028 *	0.015 *
					(0.004)	(0.004)	(0.005)
$EJOB_{i,t}$						2.00E-04 *	2.00E-04 *
						(1.64E-05)	(1.86E-05)
$EMP_{i,t}$						-3.25E-07 *	-2.47E-07 *
						(3.95E-08)	(4.00E-08)
$E/PRATIO_{i,t}$						0.039 *	0.036 *
						(0.006)	(0.006)
Nobs	3843	3843	3843	3843	3843	3843	3843
Log-Likelihood	-1662.45	-1341.16	-1339.50	-1087.51	-1055.55	-953.32	-920.16

Note: Standard Errors are in parenthesis below coefficients
Significance Levels with p<0.05=~, p<0.01=*

Table 1.3

Basic Statistics Spillover Analysis of Semiconductor Firms in Silicon Valley and Route 128

		All Sample		Silicon Valley		Route 128	
Variable	**Description**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
YEAR	Year	1986.644	7.036	1987.672	6.487	1984.875	7.573
FIRMAGE	Age of firm	15.364	15.071	12.178	13.200	20.846	16.452
FIRMAGE2	Age of firm square	463.140	1128.319	322.502	1065.042	705.077	1191.609
SILICONV	Dummy=1 if in Silicon Valley, 0 if in Route 128	0.632	0.482	1.000	0.000	0.000	0.000
TOTPAT	Total number of patents by Firm {I} in year {t}	0.900	5.923	1.014	6.950	0.704	3.507
$TIES_{t-1}$	Patent weighted tied stars to firms at {t-1}	0.053	0.619	0.081	0.777	0.006	0.094
$CUMMTIES_{t-1}$	Cummulative ties at {t-1}	0.405	4.098	0.599	5.140	0.078	0.643
$LOCTIES_{t-1}$	Patent weighted same BEA tied stars to firms at {t-1}	0.031	0.378	0.048	0.486	0.004	0.072
$CUMMLOCTIES_{t-1}$	Cummulative locties at {t-1}	0.265	2.426	0.391	3.038	0.054	0.427
$EXTTIES_{t-1}$	Patent weighted different BEA tied stars to firms at {t-1}	0.021	0.299	0.032	0.376	0.002	0.039
$CUMMEXTTIES_{t-1}$	Cummulative extties at {t-1}	0.139	1.762	0.208	2.215	0.024	0.224
$UNITIES_{t-1}$	Patent weighted untied stars to firms at {t-1}	2.607	2.887	1.318	1.418	4.777	3.388
$CUMMUNTIE_{t-1}$	Cummulative united stars at {t-1}	23.976	32.047	7.440	6.012	51.814	38.210
$UNTIELOCAL_{t-1}$	Patent weighted same BEA untied stars to firms at {t-1}	2.308	3.001	0.841	1.328	4.777	3.388
$CUMMUNTIELOC_{t-1}$	Cummulative untiedlocal stars at {t=1}	20.939	33.427	2.599	3.365	51.814	38.210
$UNTIEEXTERNAL_{t-1}$	Patent weighted different BEA untied stars to firms at {t-1}	0.299	0.458	0.476	0.500	0.000	0.000
$CUMMUNTIEEXT_{t-1}$	Cummulative untieexternal stars at {t-1}	3.037	3.337	4.840	3.002	0.000	0.000
$W*TOTPAT_{t-1}$	Average effect of neighbour firms* totpat {t-1}	8.037	11.778	9.564	13.178	5.467	8.334
$W*LOCTIES_{t-1}$	Average effect of neighbour firms*locties{t-1}	0.932	1.784	1.458	2.074	0.046	0.231
$W*CUMMLOCTIES_{t-1}$	Average effect of neighbour firms*cummlocties{t-1}	7.348	16.679	11.668	19.832	0.075	0.405
Nobs		5514.000		3487.000		2027.000	

Figure 1.5
Semiconductor Firms and Active Stars in Route 128

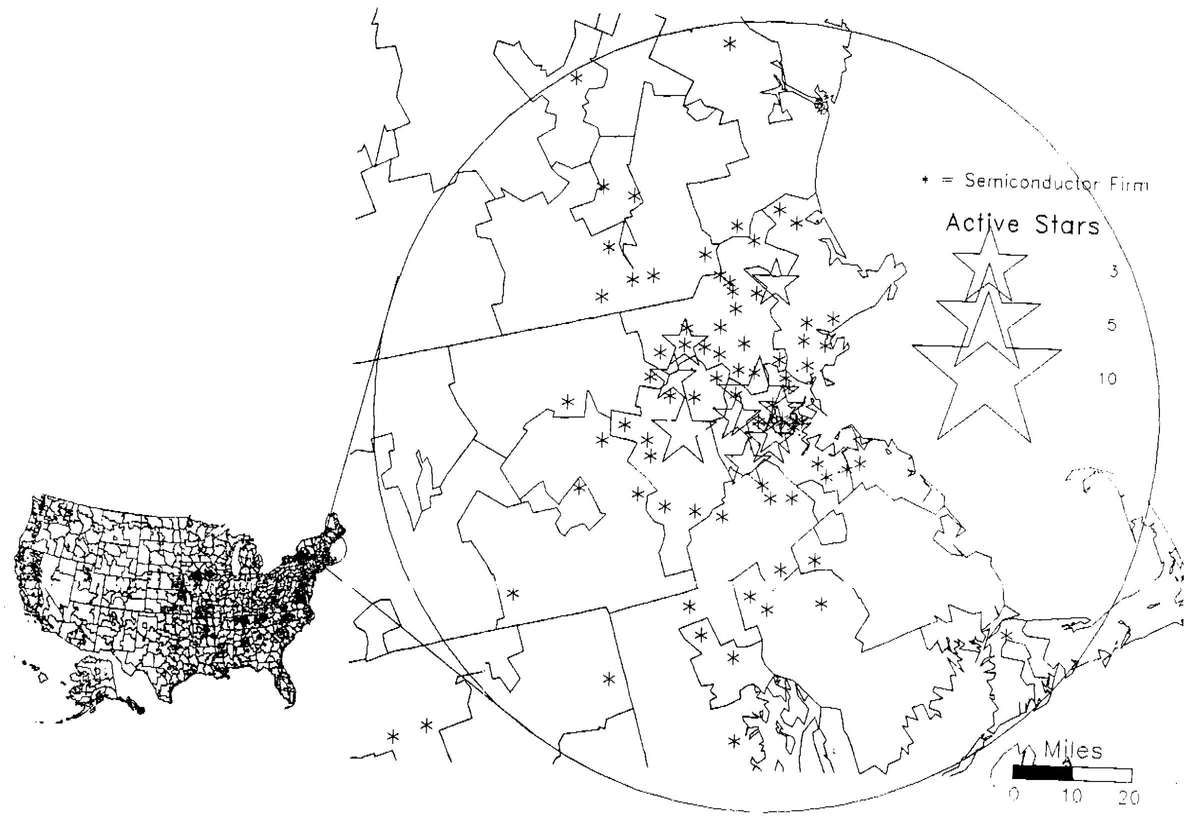

Figure 1.6
Semiconductor Firms and Active Stars in The Silicon Valley

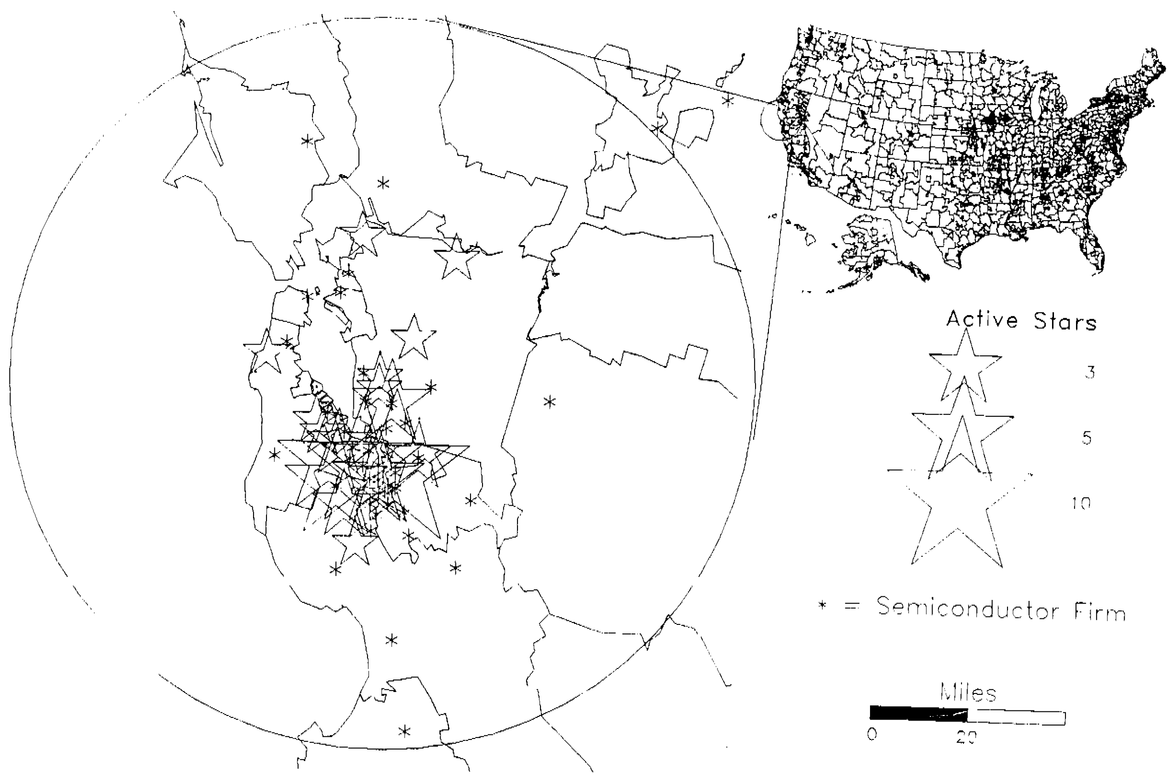

Table 1.4
Estimates for Patents Granted
Poisson Regressions, Dependent Variable: Total Patents Granted

	Yearly Ties			Cummulative Ties		
	ALL	**Silicon Valley**	**Route 128**	**ALL**	**Silicon Valley**	**Route 128**
CONSTANT	-1.177 *	-1.611 *	-1.725 *	-1.124 *	-1.309 *	-3.718 *
	(0.037)	(0.046)	(0.089)	(0.036)	(0.046)	(0.135)
$TIES_{t-1}$	0.306 *	0.307 *	1.244 *			
	(0.003)	(0.003)	(0.060)			
$UNITIES_{t-1}$	0.017 *	0.227 *	0.080 *			
	(0.005)	(0.010)	(0.008)			
FIRMAGE	0.073 *	0.096 *	0.062 *	0.061 *	0.080 *	0.167 *
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.008)
FIRMAGE2	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.003 *
	(3.50E-05)	(3.93E-05)	(7.08E-05)	(3.32E-05)	(3.73E-05)	(1.31E-04)
$CUMMTIES_{t-1}$				0.056 *	0.052 *	1.161 *
				(0.001)	(0.001)	(0.032)
$CUMMUNTIE_{t-1}$				0.002 *	0.019 *	0.023 *
				(0.001)	(0.003)	(0.001)
Nobs	5171.000	3244.000	1927.000	5171.000	3244.000	1927.000
Log-Likelihood	-13850.024	-9135.379	-4094.141	-12711.595	-8365.495	-3359.055

Note: Standard Errors are in parenthesis below coefficients
Significance Levels with p<0.05=~, p<0.01=*

Table 1.5
Estimates for Patents Granted Opening Ties into Local and External Ties
Poisson Regressions, Dependent Variable: Total Patents Granted

	Yearly Ties			Cummulative Ties		
	ALL	**Silicon Valley**	**Route 128**	**ALL**	**Silicon Valley**	**Route 128**
CONSTANT	-1.165 *	-1.509 *	-1.763 *	-1.126 *	-1.241 *	-3.859 *
	(0.036)	(0.044)	(0.090)	(0.036)	(0.043)	(0.143)
$LOCTIES_{t-1}$	0.301 *	0.299 *	2.423 *			
	(0.015)	(0.012)	(0.160)			
$EXTTIES_{t-1}$	0.313 *	0.318 *	-1.353 *			
	(0.021)	(0.018)	(0.363)			
$UNTIELOCAL_{t-1}$	0.011 ~	0.230 *	0.082 *			
	(0.005)	(0.009)	(0.008)			
FIRMAGE	0.074 *	0.097 *	0.062 *	0.063 *	0.085 *	0.180 *
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.009)
FIRMAGE2	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.004 *
	(3.51E-05)	(3.95E-05)	(7.04E-05)	(3.36E-05)	(3.87E-05)	(2.00E-04)
$CUMMLOCTIES_{t-1}$				0.037 *	0.019 *	1.009 *
				(0.006)	(0.006)	(0.059)
$CUMMEXTTIES_{t-1}$				0.083 *	0.099 *	1.742 *
				(0.008)	(0.008)	(0.183)
$CUMMUNTIELOC_{t-1}$				0.001 ~	0.014	0.024 *
				(0.000)	(0.005)	(0.001)
Nobs	5171	3244	1927	5171	3244	1927
Log-Likelihood	-13853.193	-9105.218	-4070.172	-12713.197	-8366.524	-3353.637

Note: Standard Errors are in parenthesis below coefficients
Significance Levels with p<0.05=~, p<0.01=*

Table 1.6
Spillover Effect of Neighbour Firms on Patents Granted
Poisson Regressions, Dependent Variable: Total Patents Granted

	Ties			Local and External Ties		
	ALL	**Silicon Valley**	**Route 128**	**ALL**	**Silicon Valley**	**Route 128**
CONSTANT	-1.321 *	-1.542 *	-1.717 *	-1.322 *	-1.543 *	-1.756 *
	(0.040)	(0.046)	(0.090)	(0.040)	(0.046)	(0.090)
$W*LOCTIES_{t-1}$	0.089 *	0.020 ~	-0.112	0.089 *	0.020 ~	-0.095
	(0.007)	(0.008)	(0.139)	(0.007)	(0.008)	(0.139)
$TIES_{t-1}$	0.308 *	0.308 *	1.242 *			
	(0.003)	(0.003)	(0.060)			
$UNITIES_{t-1}$	0.023 *	0.230 *	0.079 *	0.023 *	0.229 *	0.082 *
	(0.005)	(0.009)	(0.008)	(0.005)	(0.009)	(0.008)
FIRMAGE	0.076 *	0.097 *	0.062 *	0.076 *	0.097 *	0.063 *
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
FIRMAGE2	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *
	(3.54E-05)	(3.95E-05)	(7.09E-05)	(3.54E-05)	(3.96E-05)	(7.05E-05)
$LOCTIES_{t-1}$				0.303 *	0.300 *	2.417 *
				(0.014)	(0.012)	(0.160)
$EXTTIES_{t-1}$				0.315 *	0.319 *	-1.349 *
				(0.021)	(0.018)	(0.363)
Nobs	5171	3244	1927	5171	3244	1927
Log Likelihood	-13789.083	-9102.513	-4093.809	-13789.020	-9102.322	-4069.932

Note: Standard Errors are in parenthesis below coefficients
Significance Levels with p<0.05=~, p<0.01=*

Table 1.7
Competition with Neighbour Firms on Patents Granted
Poisson Regressions, Dependent Variable: Total Patents Granted

	Ties			Local and External Ties		
	ALL	**Silicon Valley**	**Route 128**	**ALL**	**Silicon Valley**	**Route 128**
CONSTANT	-1.234 *	-1.522 *	-1.803 *	-1.224 *	-1.393 *	-1.843 *
	(0.038)	(0.046)	(0.090)	(0.038)	(0.044)	(0.091)
$W*TOTPAT_{t-1}$	0.007 *	-0.017 *	0.030 *	0.007 *	-0.017 *	0.030 *
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
$TIES_{t-1}$	0.308 *	0.306 *	1.319 *			
	(0.003)	(0.003)	(0.060)			
$UNITIES_{t-1}$	0.015 *	0.277 *	0.074 *			
	(0.005)	(0.011)	(0.008)			
FIRMAGE	0.073 *	0.095 *	0.054 *	0.074 *	0.096 *	0.054 *
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
FIRMAGE2	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *	-0.001 *
	(3.52E-05)	(3.76E-05)	(7.09E-05)	(3.53E-05)	(3.80E-05)	(7.03E-05)
$LOCTIES_{t-1}$				0.302 *	0.306 *	2.503 *
				(0.015)	(0.012)	(0.160)
$EXTTIES_{t-1}$				0.315 *	0.305 *	-1.298 *
				(0.021)	(0.018)	(0.365)
$UNTIELOCAL_{t-1}$				0.010 ~	0.272 *	0.076 *
				(0.005)	(0.010)	(0.008)
Nobs	5171	3244	1927	5171	3244	1927
Log Likelihood	-13832.000	-9062.036	-4022.916	-13835.140	-9036.541	-3999.181

Note: Standard Errors are in parenthesis below coefficients
Significance Levels with p<0.05=~, p<0.01=*